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ORIGINAL ARTICLE

Depth estimation of steel cracks using laser and image processing techniques

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Abstract Crack detection is needed to maintain safety and its automation is a must when human-based inspection cannot be made due to space limitations and/or hazards. In this study, an automatic crack depth measurement method using image processing and laser methods is developed. Measurement of maximum actual depths is done using Keyence (VK-X100) laser microscope. Microscope capture crack image segments using 1/3 in. (8.5 mm) sensor color charge-coupled device (CCD) camera with high resolution and 10x constant magnification. Depths are also calculated using the updated Make3D toolbox. Measured and calculated depths are compared for 11 cracked specimens with 105 segments. The comparison showed that the minimum and overall average error between measured and calculated depths are about 6.13% and 28.22% respectively.

1. Introduction

There is always a need to develop a crack inspection model. The traditional visual inspection methods are time consuming and expensive. Automated crack inspection methods that limit the necessity of human inspection have the potential to lower the cost and time required for surface inspection. Characteristics of cracks are extracted by a high resolution camera and image processing algorithms. The limitations of the extraction can be reduced to the accuracy of sub pixel order. So, the proposed method enables not only the extraction of cracks, but also assures high quality crack analysis. Compared with other characteristics of the crack, such as length, location and width, crack depth is the most difficult characteristic to be estimated. On the other hand, the service life is the most serious problem affecting the formation of cracks due to disruptive stresses or unexpected mechanical, chemical or physical loading. Thus, crack depth is a frequently used factor when reconstruction is performed. The existing methods for crack inspection can be divided into two classes: destructive testing (DT) and nondestructive testing (NDT) methods. The DT method is time and resource consuming. The NDT methods include contact methods using impact echo or ultrasound approaches and non-contact methods using laser sensors, ground-penetrating radar, and image classification techniques [1].

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Image processing method is the only way that provides the picture of the crack in its entirety. With the adding of some more effective models, a combined approach can make it possible to provide comprehensive results about cracks depths.

This study focuses on steel surface crack depth measured and calculated values. There should be a relationship between the crack characteristics and its depth value.

2. Crack depth measuring techniques

Lu et al. [1] measured crack depth using Impact Echo Test System with accuracy within 4–10% of the measurement range. Yang et al. [2] collected echo signals by a phased array ultrasonic transducer for cracks with different orientations and depths. The feature vectors were extracted by fractal technology, peak amplitude and wavelet packet methods. Streza et al. [3] applied a changing excitation frequency from 50 mHz to 40 Hz on aluminum specimens cracks. Results showed the spatial distribution of thermal gradients for a crack depth at an excitation frequency of 0.5 Hz. This method can provide information up to a crack depth of 3 mm for aluminum surfaces. Sahoo et al. [4] used ultrasonic angle beam transducer, 2.25 MHz, 0.5 in. (12.7 mm) element diameter with a 45 wedge angle. The ultrasonic data was collected by pulse-echo method. Steel plates with cracks varying from 1 mm to 3 mm depths were checked. It was observed that as the crack size decreases from 3 mm to 2 mm, signal amplitude decreases from 78 to 48 Omniscan units. It is also observed that, as they moved closer to the crack, the time of flight of the crack signals decreases. These observations are highly important to extract useful features. Takadoya et al. [5] used a surface breaking crack of depth (a) in a steel plate of thickness (h). The crack was perpendicular to the bottom face of the plate. The plate was immersed in a water bath, and then it was exposed to an ultrasonic beam from the opposite side of the cracked surface. Different types of model cracks ranging from 0.6 mm to 2.4 mm were considered in depth and separated by 0.2 mm, and acquired their waveforms in the time and frequency domains. The depth of the crack is estimated from the back-scattered waves generated by interactions with the crack. Scattered waveforms were calculated from the surface breaking crack by theoretical and numerical analysis based on an elastic wave theory. Abdel-Qader et al. [6] proposed a comparison of the effectiveness of crack detection in the images of a bridge surface by using Fast Fourier Transform, Sobel filter, Fast Haar transform and Canny filter. The FHT is relatively new and shows promise in its ability to detect edges. Haar decomposes the image into low-frequency and high frequency components. This process is followed by isolating those high-frequency coefficients from which the edge features of an image are identified. Hutchinson et al. [7] proposed an image-based framework using optical cameras. The framework includes image processing techniques such as localization of damage at each image frame, determination of damage occurrence using time series images and geometric quantification of damage. Results showed success in monitoring and quantifying geometrically the cracks. Ito et al. [8] also proposed an automatic measurement system for inspection by means of fine crack extraction. By using a high-resolution camera, characteristics of cracks are extracted using image processing techniques. Employing threshold selection and total brightness of the crack region, the limitations of the extraction was reduced to sub pixel order of accuracy. This means the, proposed method enables not only the extraction of cracks, but also realizes high quality crack analysis. Fujita et al. [9] proposed two preprocessing methods using the subtraction method and the hessian matrix. Since the local window is fixed, these methods cannot be flexibly applied to different widths. The crack is difficult to distinguish from the images of real surfaces with noises by the conventional methods which do not use the characteristic of cracks. Moreover, the methods whose window size is fixed are inadequate to extract accurate cracks, because the length and width of cracks are different on the real surfaces. The conventional methods miss cracks while regard noises as cracks. For practical use, the accuracy of measurement for crack width is also required. Dare at el. [10] noted that an image is represented by the discrete array of pixel. The measurement with sub pixel order is performed by the bi-linear interpolation. However, the unit of measurement does not correspond to "mm" but "pixel". Chen et al. [11,12] improved the method of Dare et al. [10], and then their method of sub pixel measurement based on Difference of Gaussian, DOG, filter and quadratic curve interpolation. The crack measurement with the unit of mm is done by using the size of the specimen and the image size. Test specimen is used for the load and vibration test. The measurement of crack width to the test specimen is mainly used to evaluate durability to the load and vibration.

3. Make 3D toolbox

Make3D is a toolbox for converting 2D images to 3D ones in order to estimate the depth map. Humans can recognize visual objects such as a particular shape may be a building with the sky, grass, trees above the ground, and so on. In this model, both the relation of monocular objects to the 3-d structure, as well as relations between various parts of the image is learned using supervised learning. Specifically, this model is trained to calculate depths using a training set in which the ground-truth depths were collected using a laser scanner.

The goal is to create a 3D model from single image. Following most work on 3-d models in computer graphics and other related fields, polygonal mesh representation of the 3-d model is used, in which can be assumed the world is made of a set of small planes. In detail, given an image, first find small homogeneous regions in the image, called "Super pixels". Each such region represents a region in the scene with all the pixels having similar properties. The Markov Random Field (MRF) models the relations by the edges between neighboring super pixels. More specifically, both the 3D location and orientation of the infinite plane are parameterized on which a super pixel lies by using a set of plane parameters $\alpha \in R^3$. Fig. 1 shows any point ($q \in R^3$) lying on the plane with parameters α satisfies $\alpha^T q = 1$. The value $1/|\alpha|$ is the distance from the camera center to the closest point on the plane, and the normal vector $\alpha = \alpha/|\alpha|$ gives the orientation of the plane. R_i is the unit vector from the camera center to a point i lying on a plane with parameters α and $d_i = 1/R_i^T \alpha$ is the distance of point i from the camera center. Where i is the super pixel, α is the plane parameter, Ri is the set of rays for super pixel i and d_i is the depth of super pixel i (see Saxena et al. [13]).

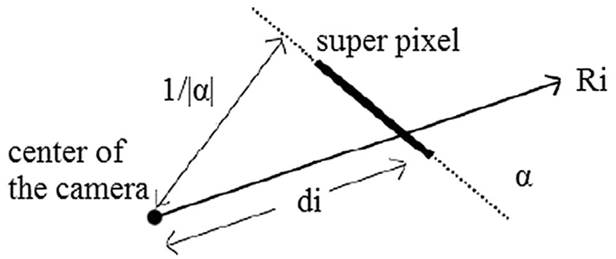

Fig. 1 Schematic of plane parameter (α) which rays (R) from the center of the camera.

3.1. Modified structure

The toolbox is updated with our condition and applied on all recorded segments. The output depth map consists of multi-level depths values. The maximum value per each segment is extracted and recorded. The updated number of pixels in x direction is 1024 pixels and in y direction is 768 pixels. The physical size of the CCD camera in x direction is updated with 4800 μm and physical size of the CCD camera in y direction is updated with 3600 μm. Camera focal length is updated with 16,500 μm. Results from the first segment for the depth estimation process (colored picture and super pixels) is shown in Fig. 2. Table 1 gives the estimated depths values for the first crack.

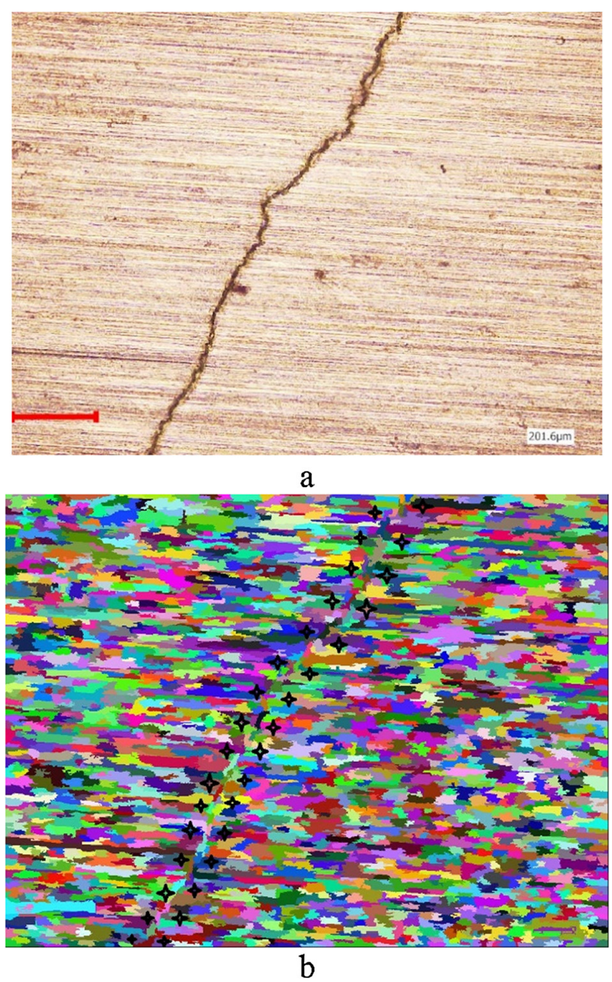

Fig. 2 Depth estimation process for first segment.

Table 1 Crack 1 Max. Estimated Depths Values (μm).

Crack segment no.	Estimated max. depth (μm)
1	37.1057
2	48.6183
3	46.5383
4	41.1307
5	46.4062
6	55.8246
7	62.7408
8	65.5736
9	38.7157
10	38.7311
11	95.6033

4. Measurement system description

Test specimens are collected from a steel fabrication factory. Due to wrong quenching process, micro cracks are generated. These cracks need to be magnified so that cracks characteristics can be extracted sufficiently. The total number of investigated cracks is 11. Each crack is segmented into 1 mm sections. Total number of segments is 105. Fig. 3 shows the first crack divided into the mentioned segments.

Measurements on a steel surface test specimens with micro cracking are applied on all recorded segments. The laser microscope is used in order to measure the crack characteristics of each segment. During capturing, no zooming is used. Only constant magnification with 10x for all segments with constant light source. Each segment picture is around 1000 (length) × 1413.9 (width) μm. Original image size is 1024 × 768 = 786432 pixels. KEYENCE is one of the leading microscopes manufacturers. The model of our laser scanning microscope is (VK-X100). Pictures are captured with 10x constant magnification using 1/3 in. (8.5 mm) (sensor size) color camera CCD image sensor with resolution of 3072 × 2304. The used lens is Nikon CF Plan 10x/0.3 EPI Infinity with 16.5 mm focal length. Constant light source is applied using 100 Watt halogen lamp. The laser scanning microscope employs two light sources: a laser source and a white light source. Fig. 4 shows its structure. These two types of light sources enable the acquisition of laser intensity, color and height that are required to construct fully-focused color images, fully-focused laser images and height information.

The test specimen surface is installed horizontally, camera and laser directions are installed vertically. The automatic adjustment and auto setting of the upper and lower limits are done at every crack segment. The final 3D profile is finally generated. Length, width, depth and surface roughness are measured and recorded per each segment. Average surface

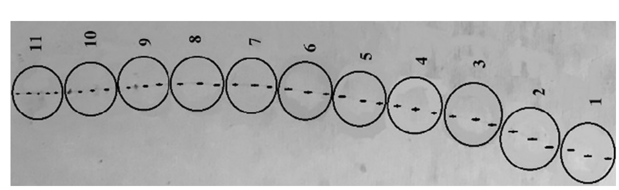

Fig. 3 Surface crack divided into one mm sections.

Fig. 4 Laser Microscope KEYENCE (vk-x100) Structure.

roughness per each segment is around 2 μm so it can be disregarded. The complete setup is shown in Fig. 5. The final result from the first segment is shown in Fig. 6. Table 2 gives the complete measurement results for the first crack.

5. Results discussion

The compared results for the maximum measured and estimated depths for crack No. 8, as an example, showed that the overall average error for estimating the actual depth using this method is 6.13%. Fig. 7 shows the measured and estimated depth profile for it. Crack No. 8 is divided into 10 segments. The maximum measured and estimated depths for all segments are 123.5 μm and 72.8 μm respectively. The minimum is 30 μm and 40.8 μm, the mean is 49.1 μm and 52.1 μm, median is 37.3 μm and 45.5 μm, standard deviation is 28.5 μm and 12.4 μm and range is 93.5 μm and 32 μm. Data analysis for maximum measured and estimated depths for Crack 8 Segments in microns is shown in Fig. 8.

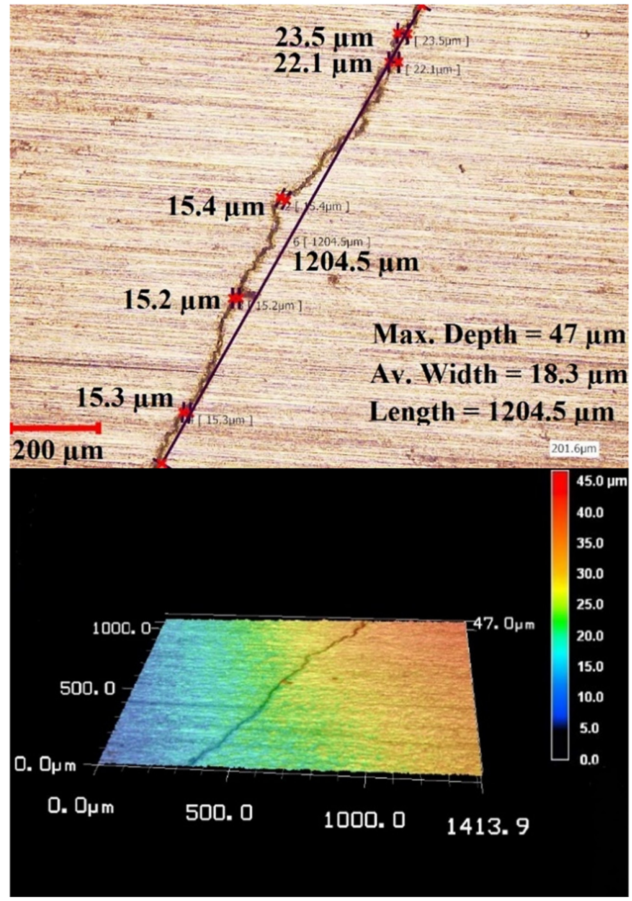

Fig. 6 Optical Crack Segment Image and depth measurement.

Table 2 Crack No. 1 measurements.

Crack segment no.	Actual max. depth (μm)	Average crack width (μm)	Length (μm)
1	47	18.3	1204.5
2	48.4	17.9	1128.5
3	46.1	20.9	1113.7
4	38.1	21.9	1071.9
5	40.5	20.2	1080.4
6	39.2	22.9	1068.3
7	41.1	20.6	1046.7
8	44.4	20.4	1060.8
9	45.3	20.9	1049.1
10	66.6	20.5	1048.2
11	64.9	35.5	1409.3

Fig. 5 Laser Microscope Setup.

The overall average error for estimating the actual depth using this method is 28.22%. Table 3 gives the average maximum depth comparison per each crack. The average maximum measured and estimated depths for all cracks are 68.8 μm and 60.2 μm respectively. The minimum is 35 μm and 32.4 μm, standard deviation (the amount of variation or dispersion of the data set) is 11.5 μm and 9.1 μm and range (difference between the largest and smallest values) is 34.2 μm and 27.9 μm. Data analysis for maximum measured and estimated depths for all cracks in microns is shown in Fig. 9.

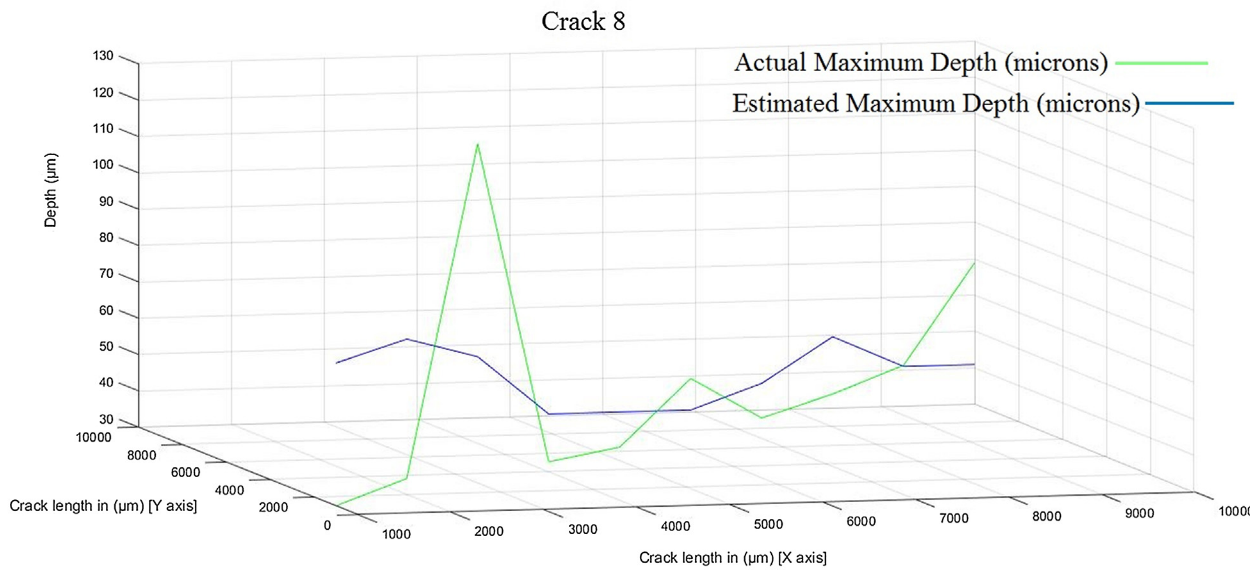

Fig. 7 Actual and estimated depth Profile (Crack 8).

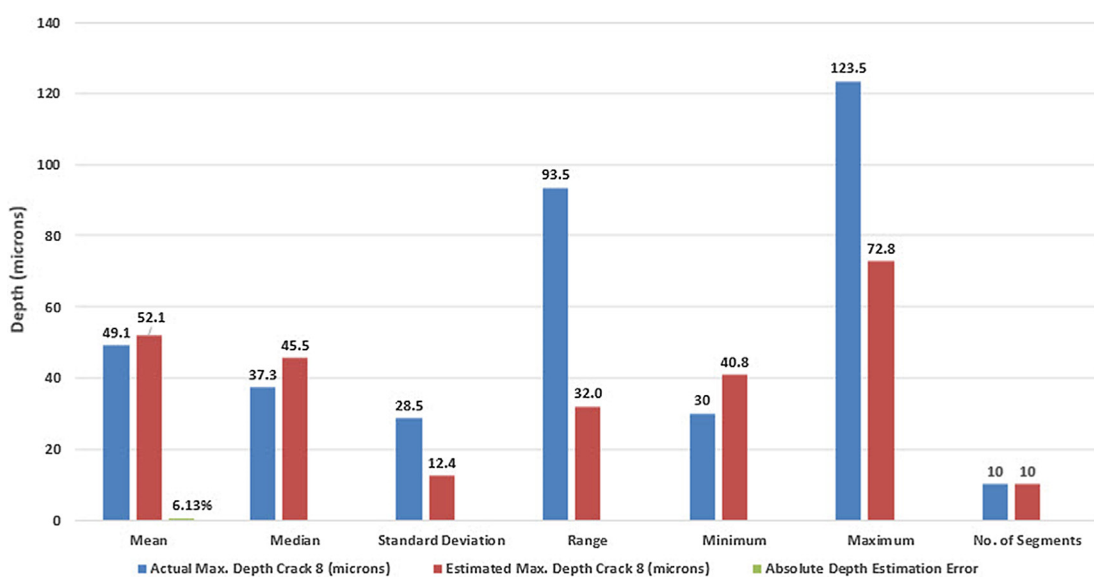

Fig. 8 Data analysis for measured and estimated depths for crack 8 (in μm).

Table 3 Average Actual and Estimated Max. Depths.

Crack no.	No. of segments	Average actual max. depth (μm)	Average estimated max. depth (μm)	Absolute average depth estimation error
1	11	47.42	52.45	10.61%
2	9	57.17	37.84	33.81%
3	18	68.84	32.36	52.99%
4	9	56.73	41.94	26.07%
5	4	63.88	44.6	30.18%
6	8	66.99	34.1	49.10%
7	10	64.82	60.21	7.11%
8	**10**	**49.11**	**52.12**	**6.13%**
9	10	56.04	44.65	20.32%
10	10	37.83	57.15	51.07%
11	6	34.67	42.64	22.99%
Overall depth estimation average error				**%28.22**

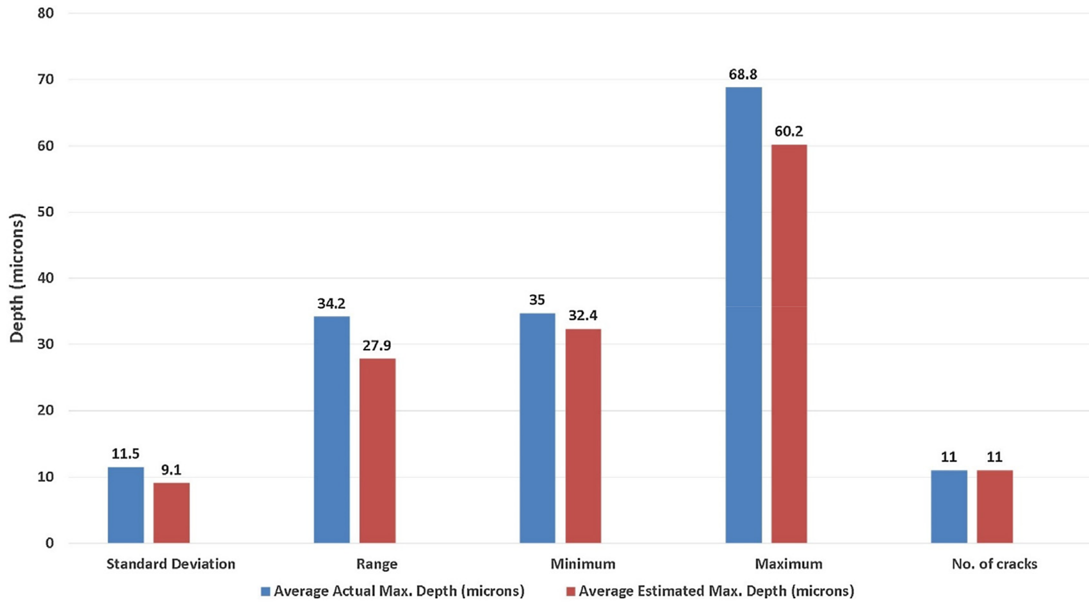

Fig. 9 Data analysis for measured and estimated cracks depths (in μm).

6. Conclusion

The maximum actual depth of steel micro cracks are measured using Keyence (VK-X100) laser microscope. The maximum estimated depths per each segment are calculated using the updated Make 3D toolbox. The total number of cracks is eleven with one hundred and five segments. The comparison showed that the minimum and overall average error between measured and estimated depths are about 6.13% and 28.22% respectively.

7. Future work

The proposed algorithm showed a good results in estimating the actual depth of steel micro cracks with a maximum depth around 1.5 mm. Neural networks are recommended to be structured and trained using these data in order to enhance the results.

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